Permeability Estimation from Well-LogDatain a Gas Carbonate Reservoir, Persian Gulf

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Abstract

Combined Magnetic Resonance log(CMR), Fuzzy Logic and three empirical methods are used to estimatepermeabilityfrom well-log data in South Pars Gas Field, a carbonate reservoir in the Persian Gulf. Comparison of the CMR derived permeability with core permeability revealed a 0.35 and 0.12 value for the C coefficients in Schlumberger Doll Research (SDR) model and Timur-Coates model respectively. The results show that the empirical methods may not have sufficient accuracy, however, Coates-Dumanoir (R^2= 0.38) empirical equation provides the best result. The CMR method and Fuzzy Logic method can estimate permeability better than Wyllie and Rose equation and Coates equation. It is concluded that Fuzzy Logic method (R^2=0.42) predicts more accurate permeability than CMR log (R^2= 0.4).

Keywords: Permeability; South Pars Gas field; Fuzzy Logic; Empirical Equation; Well-log data

1. Introduction

Petrophysical evaluation includes determining the properties of reservoir rock (porosity, water saturation, shale volume and lithology) using processing and interpretation of well-log data. Results of such studies are used for modeling the reservoir. Porosity and permeability of reservoir rocks are important physical properties related to storage and fluid transmission (Tiab and Donaldson, 1996).Permeability estimation from well-log data is an effective and cost efficient method.Several techniques have been used to estimate permeability from well-log data on the basis of mathematical pattern recognition, simplifying assumption and calibration with a data set of different lithology. These studies include poro-perm cross plots (Tiab and Donaldson, 1996), principal component analysis, PCA[1], (Lee and Datta-Gupta, 1999), cloud transforms (Al Qassab et al., 2000), neural networks (Helle et al., 2001)and genetic algorithms, GA[2] (Cuddy and Glover, 2002). The poro-perm cross-plot plots provide best results in absence of lithological variation. PCAuses a mathematical procedure to transform a setof (possibly) correlated variables into another (smaller) setof uncorrelated variables called principal components. The principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible (Bishop,1996; Bell and Sejnowski, 1997). PCA is mostly used for making 2-D plots of data for visual interpretation.The Cloud transform reproduces the conditional distributions of a dependent 3D parameter given an independent 3D parameter. The estimated distribution is used as the basis for the cloud transform. The relationship between porosity and permeability is found to be non-linear and cloud transform technique is applied for permeability distribution(Al Qassab, 2000).

Artificialneural network is an empirical approach that estimates the reservoir parameters, quantitatively.Well-log data is used as input and the network is trained to determine the output data through non-linear relationships(Yang et al., 2004). Neural networks require the correct amount of conditioning. In addition, neural networks are very

[1]principal component analysis, PCA
[2]genetic algorithms, GA

hard to ‘‘figure out’’ and are, therefore, often regarded as ‘‘black boxes.’’ GAisan effective search methodbased on the principles of natural selection and genetics(Kadkhodaie-Ilkhchi et al., 2006). GAis commonly used for permeability prediction from well-log data. The method is a simple tool for confirming the correlation. It is also applicable in the lack ofcore samples and/orextensive logging data (Brown et al., 2000).

In this study,the CMR[1], the Fuzzy Logic method, and three empirical methodswere applied to estimate permeability from well-log data ofKangan and DalanFormations. The results compared with core permeability as a standard reference. The CMR tool provides the distribution of grain sizes or pore sizes within the rock by inverting theT_2 relaxation time spectrum. These data are expected to be extremely useful to provide predicted permeability.Fuzzy results are completely open and easy to understand and relate to the problem at hand. Although interpreting fuzzy results is simple, they often describe complex nonlinear systems that would defy conventional logic. In the empirical methods, mathematical functions relating the desired permeability based on several well log data inspired by theoretical concepts are used. This approach has long been favored in the field and much effort has been made to understand the underlying petroleum engineering principles.

2. Methodology

For Permeability estimation,porosity is predictedusingCMR and conventional logs. The results are used to CMR log, Fuzzy Logic and empirical methodsto estimate permeability.

The benefits of wire-line logging are obvious, the measurements are performed in a static environment, the contact between the tools and the formation is good, the depth control is excellent, and the tools used are proven through several decades of operations (e.g. Bassiouni, 1994). Caliper (CALI)[2], gamma ray (GR)[3], neutron (NPHI)[4], density (RHOZ)[5], sonic (DT)[6] and resistivity (RLA0, RLA1, RLA5)[7] well logs were used inthis study.The CMR, core porosity and corepermeability of well A, South Pars Gas Field, were also used. The following section presents a brief description of themethods used in this study.

2.1 Density-Magnetic Resonance Porosity (DMRP)[8]

[1]Combined Magnetic Resonance log
[2]Caliper
[3]Gamma Ray log
[4]Neutron log
[5]Density log
[6]Sonic log
[7]Resistivity logs
[8]Density-Magnetic Resonance Porosity

An empirical method, designated as DMR, combines density porosity and nuclear magnetic resonance (NMR)[1] porosity to improve the estimation of gas porosity. In gas reservoir, the porosity resulted from density log (DPHI)[2] is indicated morethan the real porosity of the formation, because bulk density measured from formation reduces due to the presence of gas. Gas presence on TCMR[3] is reversely related to DPHI, as the total porosity of formation is underestimated because ofthe lowhydrogen index (HI)[4] and insufficient polarization of gas(Freedman et al., 1998).NMR porosity along with density is a good tool for gas-corrected total porosity calculations and is independent of facies.

$DMRP = 0.6DPHI + 0.4TCMR$(1)

Where, *DMRP* is the gas-corrected total porosity, *TCMR* is total porosity resulted from CMR log (%)and *DPHI* is porosity resulted from density log (%).

Equation 1is a simple rule that can be applied by visual inspection to the DPHI and TCMR logs for predicting DMRP. Greater weight dedicated to DPHIdue to the lower influence of gas on DPHI than TCMR (Freedman et al., 1998).

2.2 Permeability derived NMR

The nature of porosity can be recognized using the NMR log, so it can be more accurate than theother indirect methods. When predicting the NMR permeability it must be remembered that the more the pores, the greater the permeability is (Hassall et al., 2004).Timur-Coates model and SDR model are two famous models for determining the permeability from NMR.

Using CMR log, these models yield a relatively accurate assessment of permeability. The following section describes these models in more details.

2.2.1 SDR[5] model

Using the SDR model, permeability is expressed as:

$K = C.T_{2LM}^{2}.\emptyset_{NMR}^{4}$(2)

Where,

K[6]is permeability (md); ϕ_{NMR}[7] is total porosity resulted from CMR log (%) and T^{2}_{LM}[8] is logarithmic meanT_2 (msec).C[9] is a coefficient based on the core permeability data (Cao Minh et al., 1997).One complication of this

[1]Nuclear Magnetic Resonance log
[2]Porosity resulted from density log
[3]Total porosity resulted from CMR log
[4]Hydrogen index
[5]Schlumberger Doll Research
[6]Permeability
[7]Total porosity resulted from CMR log
[8]Logarithmic meanT_2
[9]Coefficient

model is its sensitivity to hydrocarbon (particularly light oil and gas). The T_2 relaxation of hydrocarbon is to some extent different from water, therefore it will influence logarithmic mean T_2 (T_{2LM}) (Al- Ajmi et al., 2001).

2.2.2 Timur-Coates Model

In this model, experimental cutoff is used for separating the bound volume irreducible (BVI)[1] from free-fluid volume (FFI)[2]. This cutoff is set as 33ms for sandstonesand100ms for carbonate.This model has no sensitivity to hydrocarbon present in the reservoir (Al- Ajmi et al., 2001).

$$K = C \cdot (\frac{FFI}{BFV})^2 . \emptyset_{NMR}^4 \qquad (3)$$

Where K is permeability (md), FFI is free-fluid volume(fraction), BVI is bound volume irreducible(%) andϕ_{NMR} is total porosity resulted from CMR log (%).

2.3Fuzzy Logic method (FL)[3]

LotfiZade (1965) showed that uncertainty may be due to fuzziness (possibility) rather than probability. FL is appropriate to deal with the nature of uncertainty in system and human errors, which were not considered in existing reliability theories (Nikravesh and Aminzadeh, 2003). Generally, geological data are not clear-cut andarehabitually associated with uncertainties. For example, prediction of core parameters from well log data is difficult and is usually associated with error (Kadkhodaie-Ilkhchi et al., 2006). FL derives useful information from this error and applies it as a powerful parameter to improve thepredictionaccuracy.A Fuzzy Inference System (FIS)[4] is a way of mapping an input space to an output space using fuzzy logic (Matlab User's Guide, 2004).

2.4Empirical methods

Empirical methods are based on determining the permeability coefficient using empirical Darcy´s law. They reveal the fundamental trend of changes in permeability coefficient a function of depth (Tavenas et al., 1986).

2.4.1 Wyllie and Rose Equation

Wyllie and Rose (1950) equation links permeability, K,porosity,$\emptyset$[5]and irreducible water saturation, S_{wirr}[6],:

$$K= C \frac{\emptyset^D}{\mathrm{Swirr}^E} (4)$$

[1]Bound volume irreducible
[2]Free-fluid volume
[3]Fuzzy Logic method
[4]Fuzzy Inference System
[5]Porosity
[6]Irreducible water saturation

Different researchers introduced different exponents and coefficient based on core analysis studies as indicated in the following table (Coates and Dumanoir, 1974).

Table1. Different exponents for Wyllie & Rose equation

C (Coefficient)		**D**	**E**	
Oil	**Gas**			
250	79	3	1	**Morris-Biggs(1967)**
___	100	2.25	1	**Timur(1968)**

2.4.2 Coates and Dumanoir Equation

Coates and Dumanoir (1974)introduced the following equation for calculating the permeability.

$$K= [(\frac{\emptyset}{Swirr})^{w}]^{2} \quad (5)$$

2.4.3 Coates Equation

Coates proposed the following equation (Balan et al., 1995) for permeability determination:

$$K= [C\frac{\emptyset^{2}(1-Swirr)}{Swirr}]^{2} \qquad (6)$$

3. Results and Discussion

This study is focused on the Iranian part of South Pars Gas Field, the world's largest non-associated gas accumulation, located in the Persian Gulf, between Qatar and Iran at about 100 km from Iranian shoreline. The Upper Permian to Lower Triassic Dalan and Kangan Formations (equivalent to Khuff formation) are two main condensate and gas-bearing reservoirs in this field (Aali et al.,2006; Rahimpour-Bonab, 2007). The reservoir consists of calcite, dolomite, and some anhydrite and shale, as the main lithology.

3.1 Data Description

The formation evaluation was carried out through about 380 meters core analysis and comparison with well-log data. To improve evaluation, the reservoirwas divided into 8 petrophysical zones, based on the trend of porosity logs (NPHI, RHOZ, DT), gamma ray (GR) and resistivity logs (RLA0, RLA1, RLA5).

3.2Estimation of porosity type

By comparing the cross plot of core porosity versus core permeability Fig. (1-b) with Fig. (1- a), the type of porosity can be determined among interparticle, moldic, vuggy and to some extent the fractured. Such porosity type has good capability for predicting the petrophysical parameters (Tiab and Donaldson, 1996).

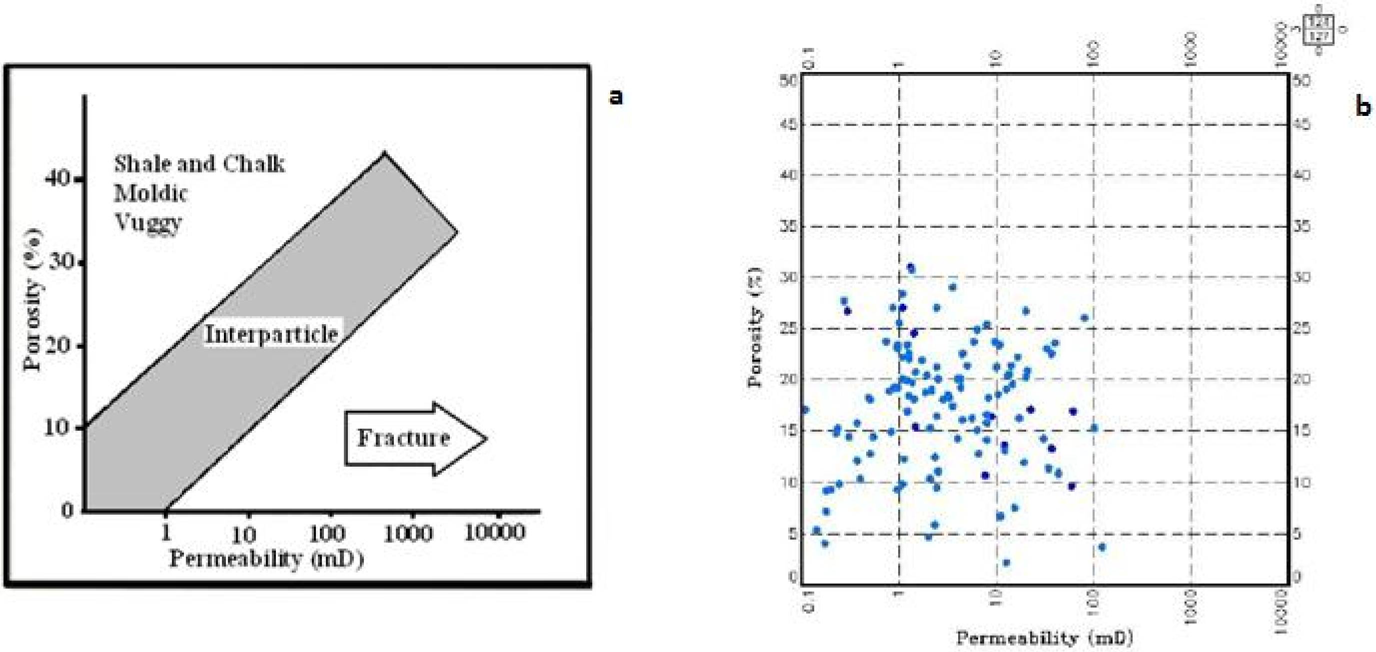


Fig. 1 a) Cross plot of core porosity versus core permeability

b)Cross plot of core porosity versus core permeability in our well

3.3 Estimation of porosity

3.3.1 Density – Magnetic Resonance Porosity (DMRP)

Using equation, 0.7 and 0.3 are obtained as the DPHI and TCMR coefficients, respectively. More weight was dedicated to DPHI due to the reduced effect of gas on DPHI rather than TCMR. For example:

DMRP= 0.7 *0.284 + 0.3* 0.103= 0.2297

The DMRP versus core porosity cross plots (Fig. 2) show that the coefficient of determination, (R^2), resulted from 0.7 and 0.3 coefficient in equation (1) is about 0.82 while that of 0.6 and 0.4 is about 0.78. Figure 3compares DPHI, TCMR and DMRP porosities with core porosity.

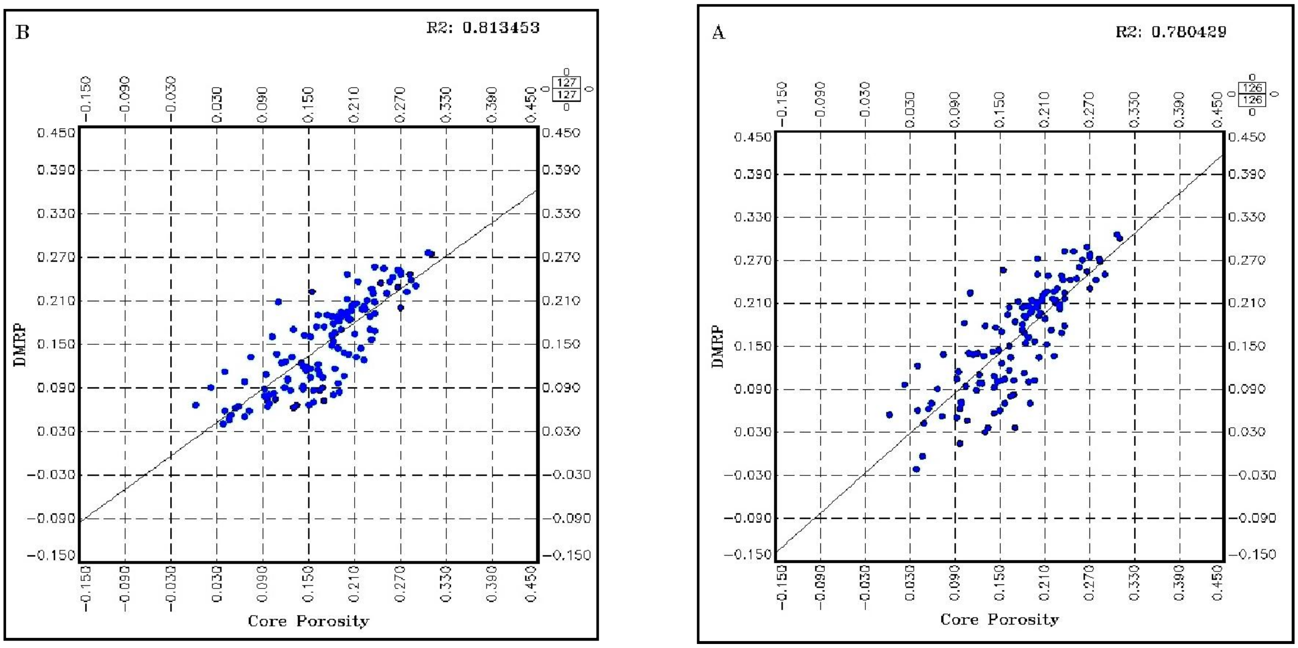


Fig. 2. Cross plots of DMRP versus core porosity

A) Resulted from 0.6 and 0.4 coefficient

B) Resulted from 0.7 and 0.3 coefficient

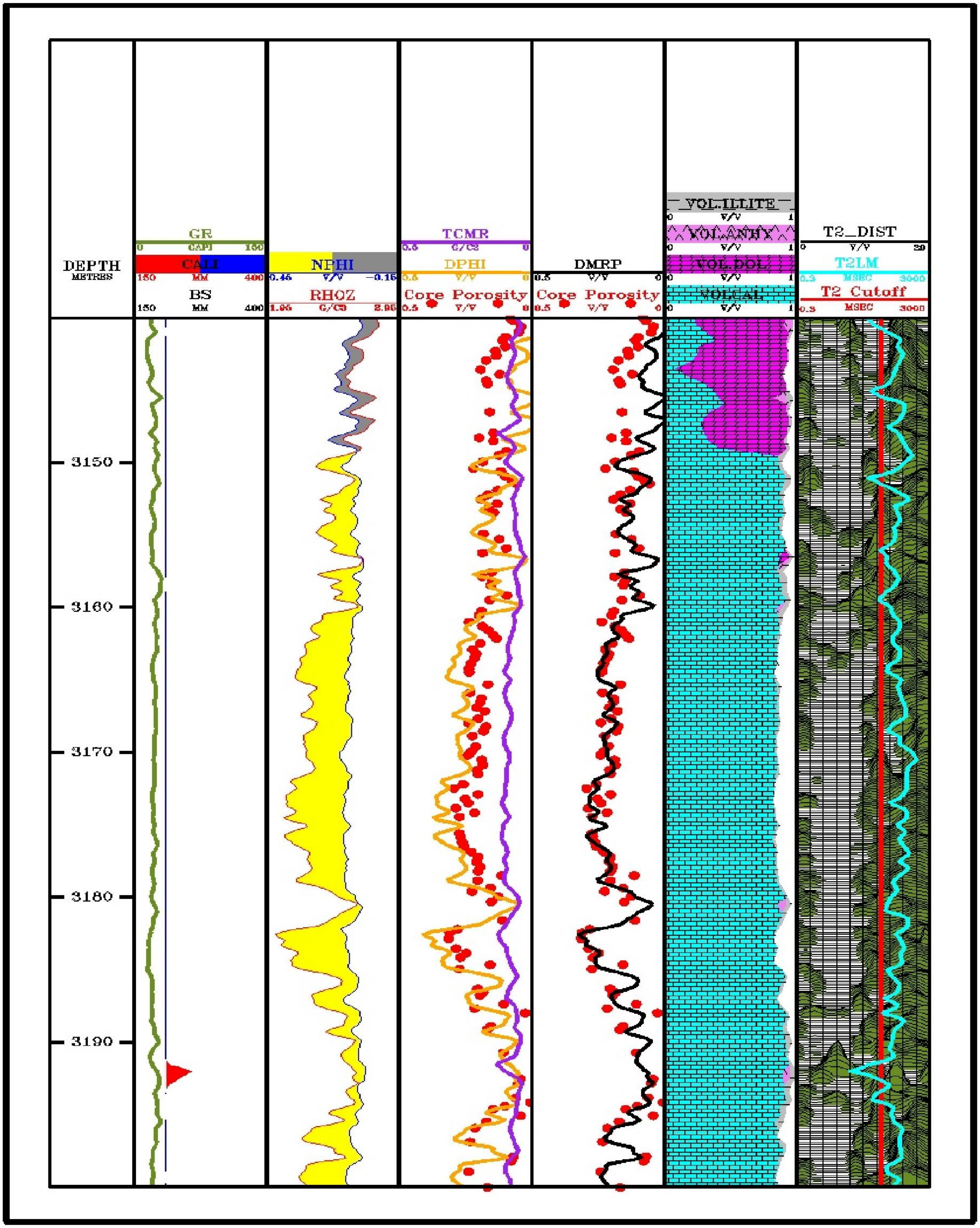


Fig. 3. Comparison of DPHI, TCMR and DMRP porosities with core porosity

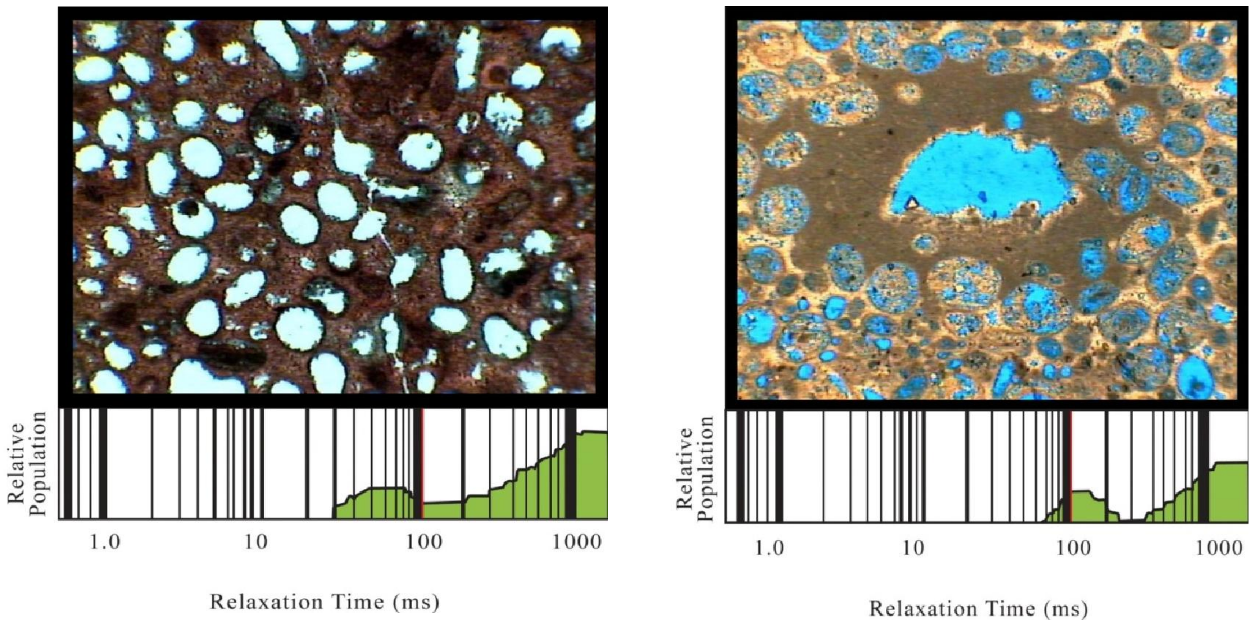
3.4Combination of T_2 Distribution and Thin-Section

In this part, the ability of CMR tool is used in assessing pore-size distribution, pore system, porosity, permeability and fluid distribution using a combination of T_2 distribution and thin-sections of the analogous depth (Fig. 4).

Sample A is a medium-grained ooidalgrainstone containing oncoid with inter-particle, intra-particle and moldic porosity that is formed in the CF5 facies from K_4 zone. Isopachous cement isobserved around non-skeletal grains. The permeability and porosity is measured as 1.3 mD and 18%, respectively. The presence of moldic and inter-particle porosity was approved by shifting the T_2 curve to the right.

Sample B is a medium-grained bioclastooidalgrainstone with macroporosity related to molds of dissolved bioclasts. Spar calcite cement occurs within molds. The permeability and porosity is measured as 1.4 mD and24.5%, respectively.Macroporosity in dissolution molds causesthepresence of free-fluid which was approved by shifting the T_2 curve to the right. Small curve in the left of the T_2 cutoff is related to capillary bound waterin small pores.

Sample



ASample B

Fig. 4. Combination of T_2 Distribution and Thin-Section.

3.5 Estimation of Permeability

3.5.1 CMR Log- In this study the permeability is calculated by SDR and Timur- Coates models. First, C coefficient is set by default as 4 for SDR model and 1 for Timur- Coates model (Equation 2 and 3). For example, a calculation of these two methods hasbeenused in this study when T^{2}_{LM} is 2.35 msec. C is 4 andϕ_{NMR} is 0.0045 from Eqs. 2, K_{SDR} will be equal to 90.565. FFI is 0.000007 %, BFV is 0.00449 %, C is 1 and ϕ_{NMR} is 0.0045 % from Eqs. 3, K_{Timur} will be equal to 9.225.

The resulted permeability cross plots are shown in Fig. 5. Then, C coefficient is improved by trial and error and comparison with core points.

Finally, the C value is estimated as 0.35 and 0.1, for SDR and Timur- Coates models, respectively. Porosity is one of the main parameters for calculating the permeability. In such equations, TCMR porosity was used once and DMRP porosity once. As indicated in Figure 6, Timur-Coates permeability resulted from combining DMRP is the best fit with data resulted from core analysis. This indicates that Timur model is more sensitive to changes of petrophysical specification of formation than SDR model.

As indicated in Figure 6, at the depth of 3140meter the core permeability is more thanSDR and Timurdue to open horizontal fractures of the dolomite zone.

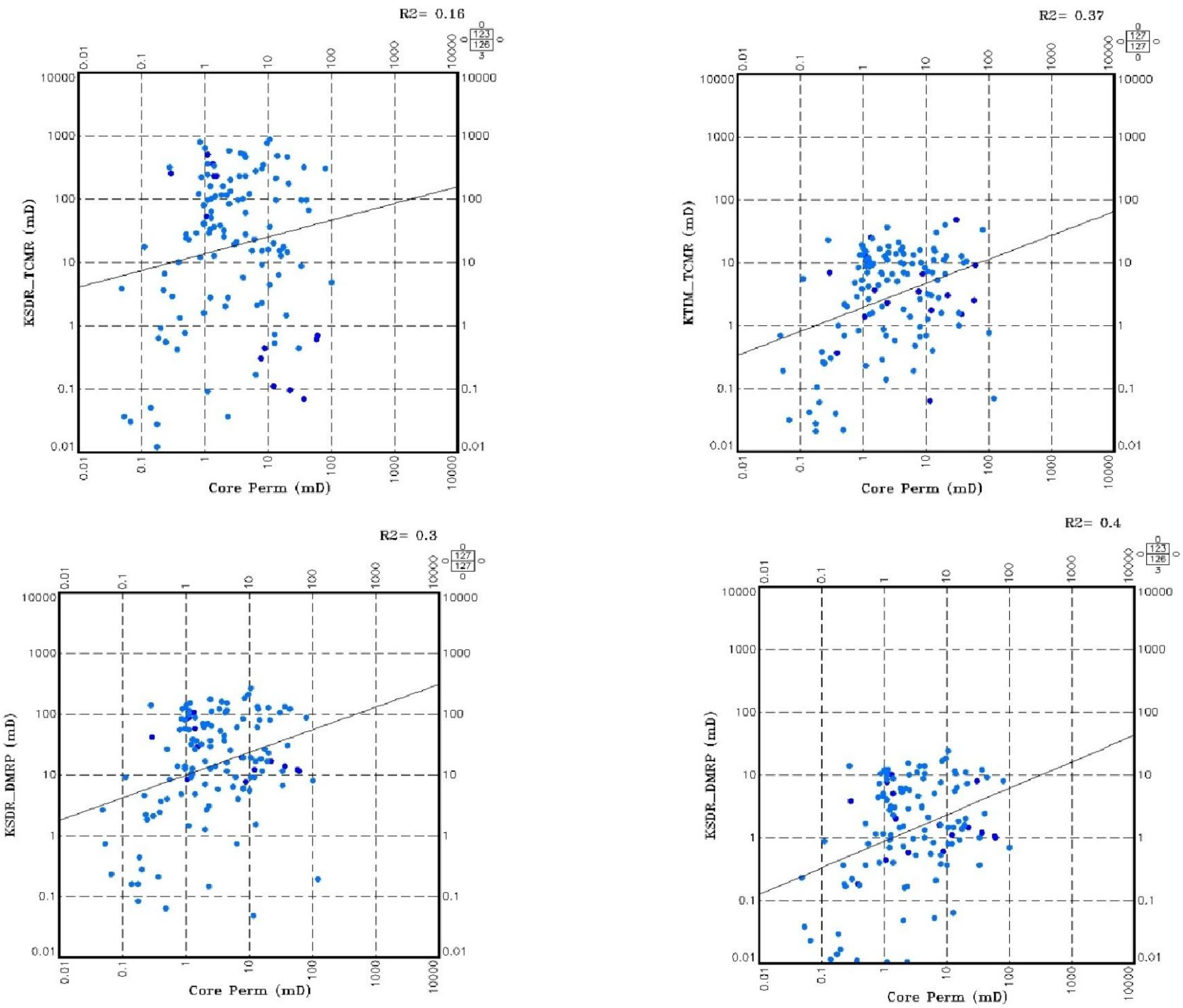


Fig.5. Permeability cross plots to comparison the estimated permeability with core permeability.

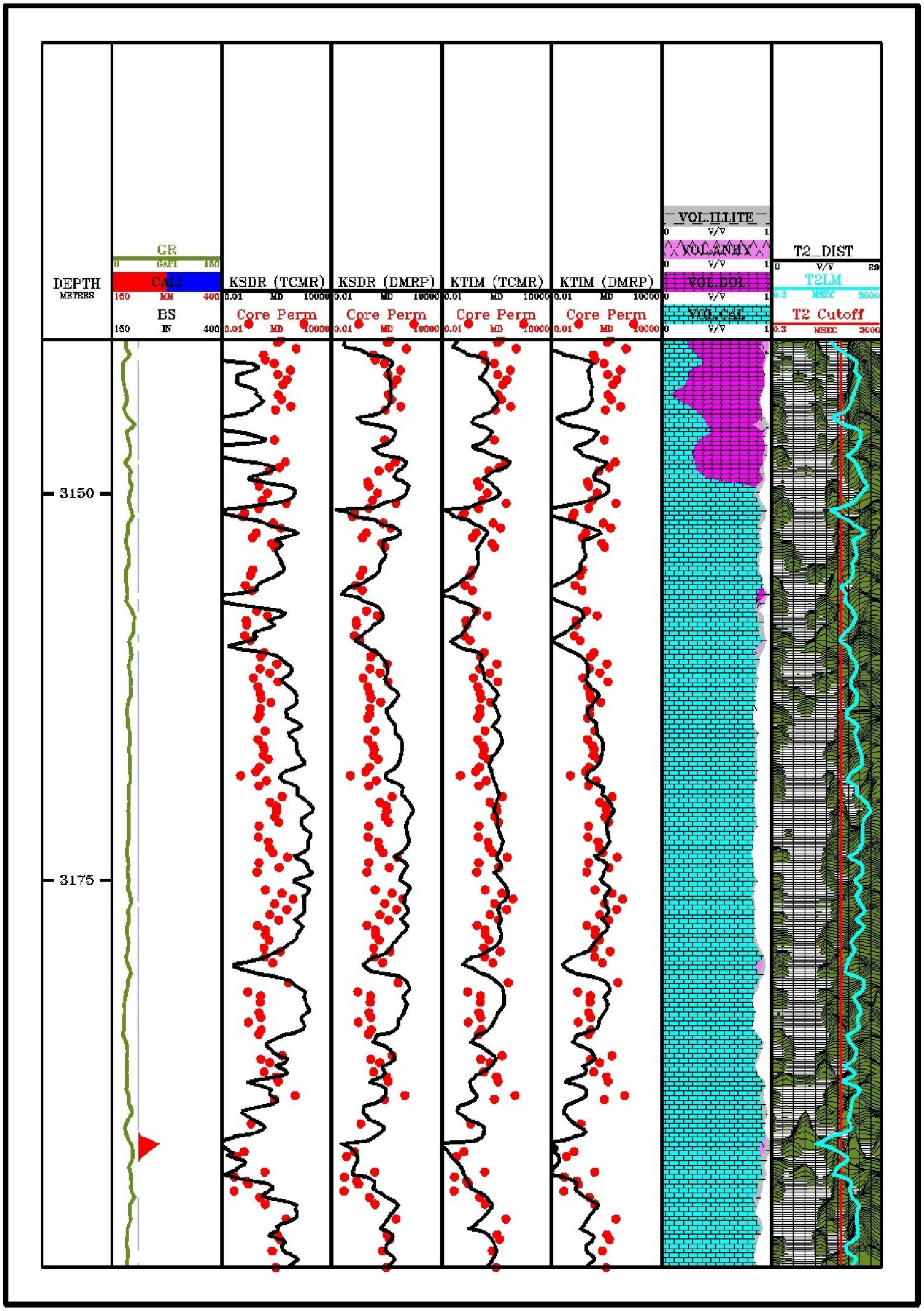


Fig. 6. Comparing permeability obtained from SDR and Timur-Coates models with core permeability

3.5.2 Fuzzy Logic- The fundamental discussion on the fuzzy theory is the discussion of membership function and how to define it. When conducting this study based on the distribution of petrophysical data on studied reservoir (e.g. porosity, resistivity logs) normal distribution (Gaussian) function has been used as a membership function. Normal distribution curve is used for predicting the relative possibility or fuzzy possibility of attributing data to one part of a set (Cuddy, 2000).

Core permeability data was first divided into ten equal sets with logarithmic scale. The number of sets depends on the number of core permeability data. Then each set is compared with petrophysical data. Petrophysical data proportional to each set will be analyzed and mean and standard deviation of each set is calculated.

To estimate the reservoir permeability, lab and descriptive data for core of well A were used to prepare fuzzy model. By conducting the sensitivity analysis on input data, the relative importance of data for predicting the permeability was determined. Porosity, shale volume and resistivity were determined as the most important parameters for estimating the permeability-Fuzzy model was tested in well A. Comparison between core permeability and permeability obtained by fuzzy logic is presented in Figure 8. The corresponding Correlation coefficient 42%, indicates the relative predominance of fuzzy method rather than NMR method and Empirical methods for estimating the permeability.

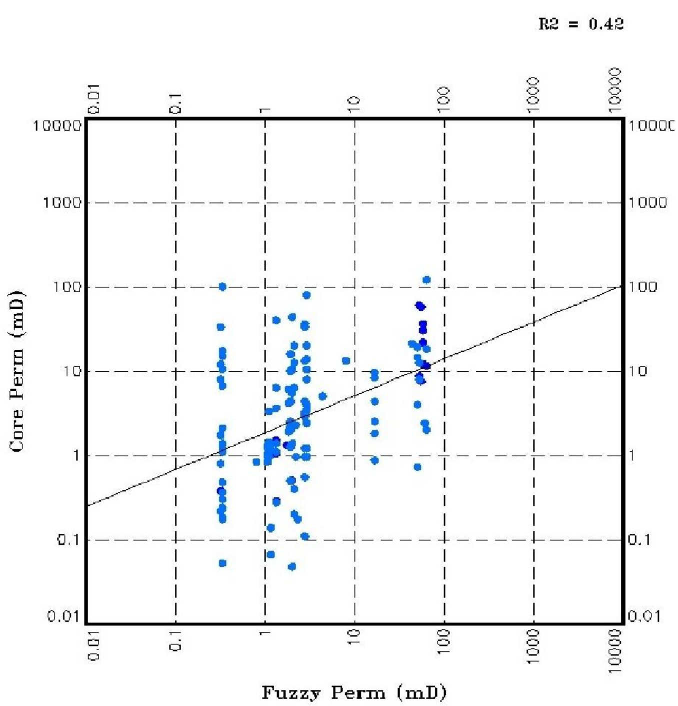


Fig. 7. Cross plot of permeability obtained from fuzzy logic versus core permeability

3.5.3 Willey and Rose Equation-Permeability calculated by Morris-Biggs and Timur formula using coefficients of Table 1had very high error, further, in all points permeability was near to zero.

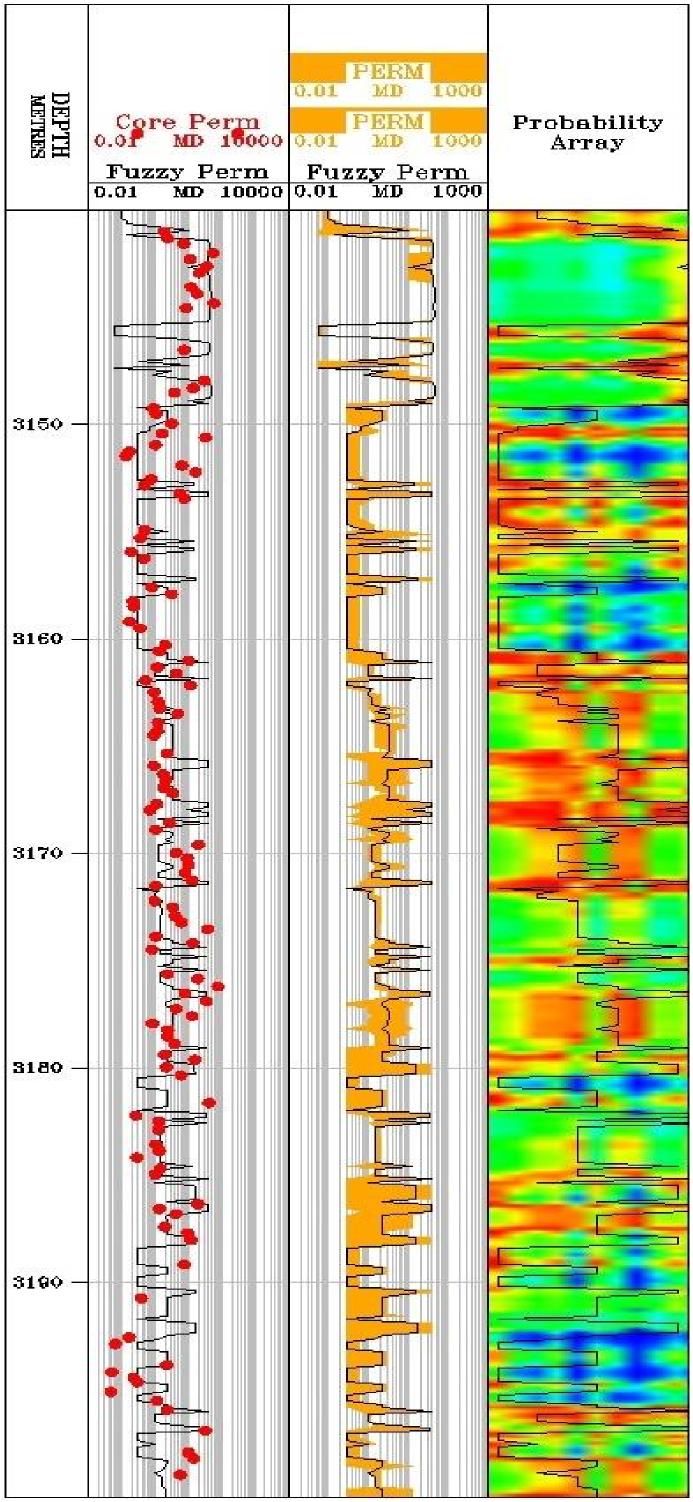


Fig. 8. Permeability obtained by fuzzy logic

Then core permeability wasdrawn on permeability curves by both formulas. These coefficients were calculated by trial and error method by both formulas which resulted in the highestconformity with core points. Finally, coefficients C, D and E for Morris-Biggs and Timur formula in well A were obtained (Table 2).

Table.2. coefficients C, D and E for Morris-Biggs and Timur formula

C		D		E		Formulas
Dolomite	**Calcite**	**Dolomite**	**Calcite**	**Dolomite**	**Calcite**	
90	210	2.9	3.1	3.8	0.5	**Morris-Biggs (1967)**
150	5	2.21	2.3	1.2	1.17	**Timur (1968)**

3.5.4 Coates and DumanoirEquation Figure9 indicates the results of Eq.5. Permeability by Coates and Dumanoirwascalculated such that coefficient C was considered by default to be about 300 and the numbers had very high error. Core permeability on permeability curves were drawn by Coates and Dumanoir formula. This coefficient in the formula was calculated by trial and error method and attainedthe highest conformity with core points. Finally coefficient C for the dolomite zone was 315 and for the calcite was 8.

3.5.5 Coates Equation-Figure 9 indicates the permeability calculated by Eq.6 versus core permeability. Permeability by Coates formula was calculated such that coefficient C by default was considered about 70 and numbers had very high error. Thecorepermeabilitywas then drawn on permeability curves from Coates formula. This coefficient in the formula was calculated by trial and error method, which had the most conformity with core points. Finally, coefficient C for the dolomite zone was 95 and for calcite was 5.

By drawing the core porosity versus porosity resulted from CMR (TCMR), it was concluded that porosity trends have no conformity with each other and this is due to the gaseous state of the studied reservoir; therefore, a parameter called DMRP which has an acceptable correlation coefficient (R^2= 0.78) was used for estimating the porosity (Fig. 3).

Coefficients obtained by DMRP 60-40 equation (Eq. 1) for DHPI and TCMR are 0.7 and 0.3 respectively; this equation indicates that gas-corrected total porosity is the weighted sum of DPHI and TCMR porosity. In this equation, more weight has been assigned to DPHI and this is due to the reduced influence of gas effect on DPHI compared to TCMR. Formula provided for DMRP in this study is indicated as:

DMRP= 0.7*DPHI + 0.3*TCMR

Because conformity of DMRP porosity with core porosity is comparable to PHIT and PHIE porosities, it can be concluded that when there is no PHIT and PHIE porosities, DMRP porosity can be used for estimating the porosity. Further, since porosity resulted from NPHI and DPHI diagrams are influenced by gas, DMRP porosity can be used for predicting the porosity.

T_2 distribution curves were interpreted for pore-size distribution, pore system and distribution of porosities in the reservoir rock and then by comparing the results with thin-section, their accuracy was approved.

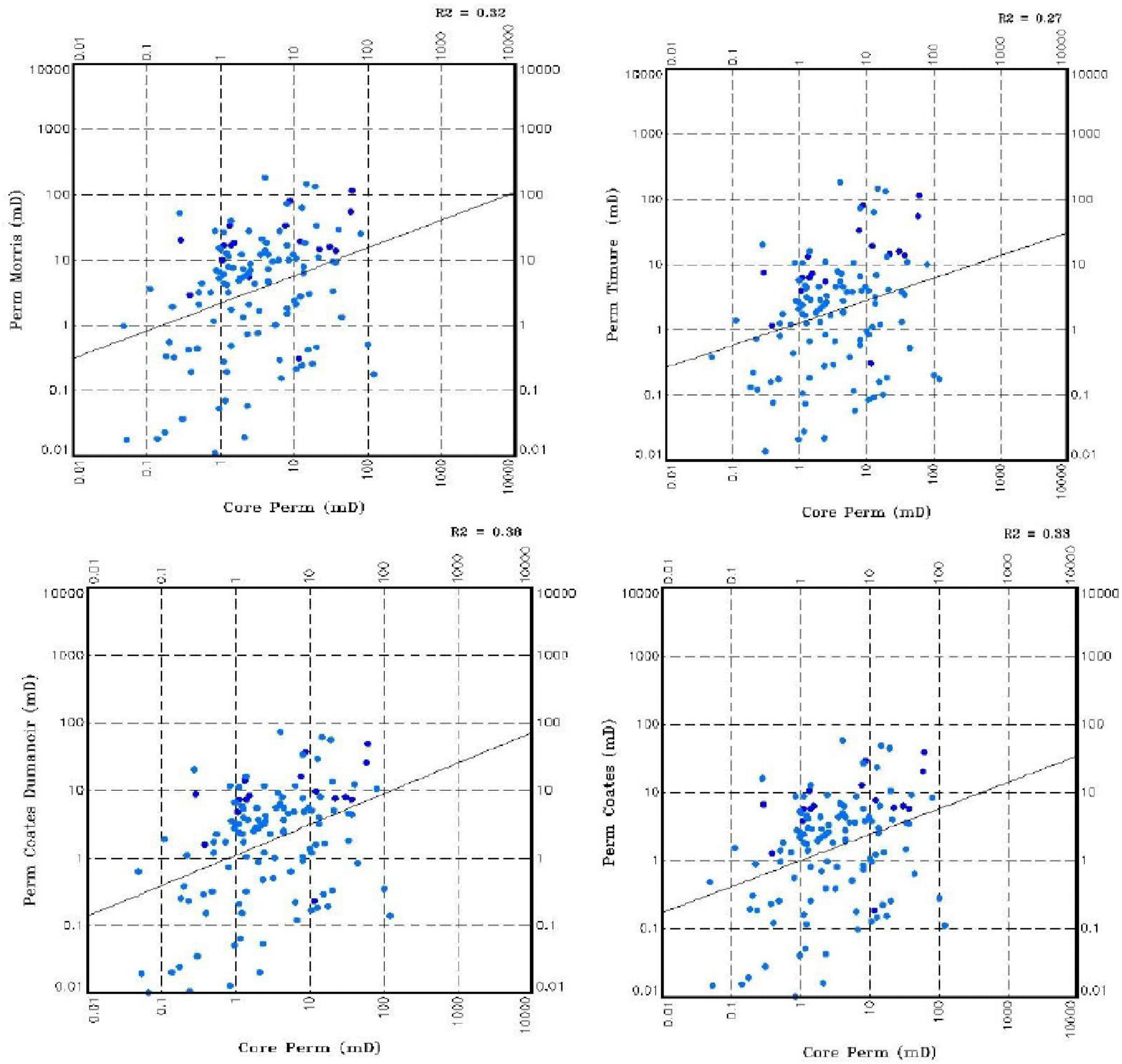


Fig.9. Permeability calculated by empirical formulas versus core permeability.

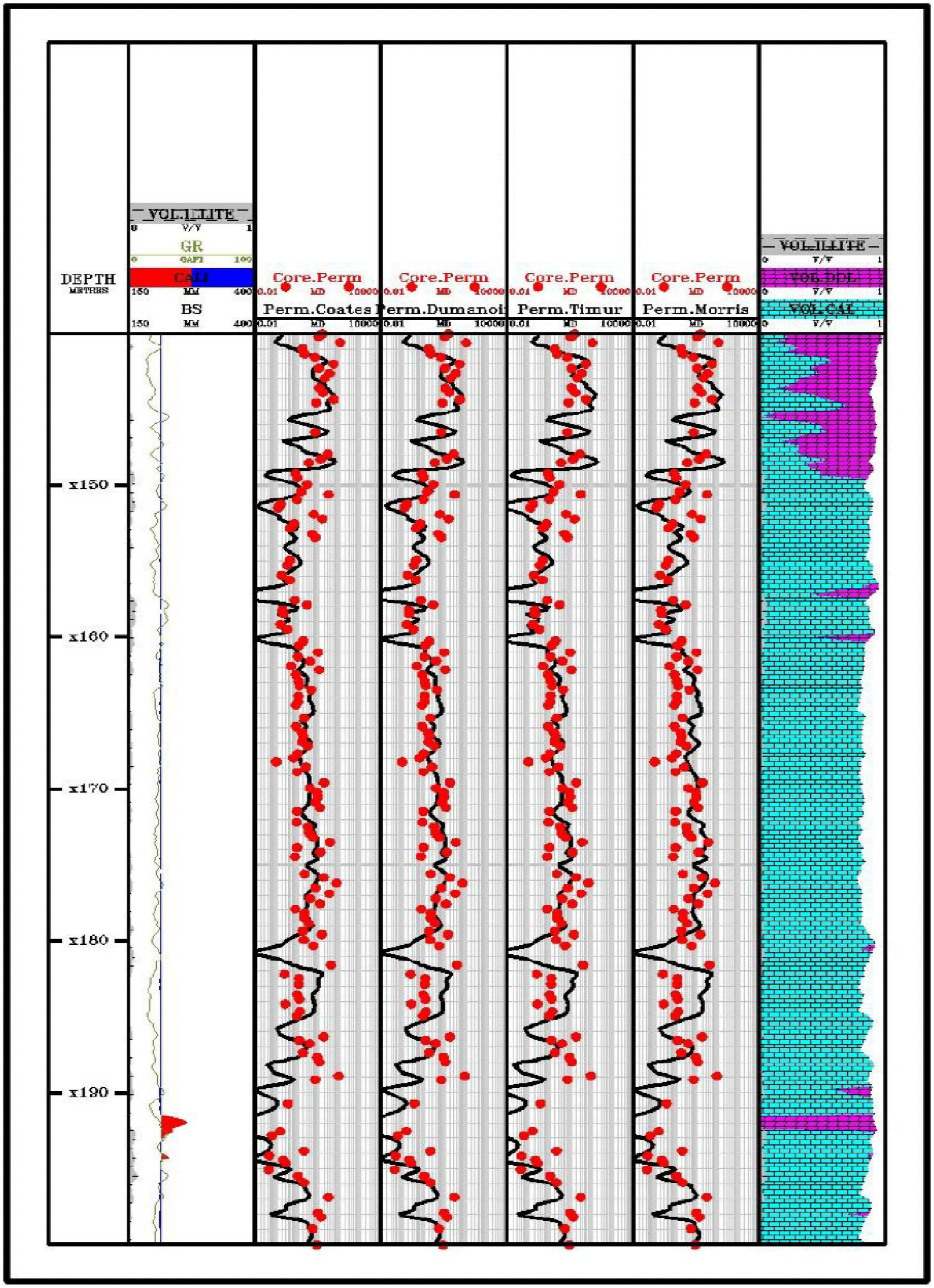


Fig.10. Results of the permeability obtained by empirical methods

4. Discussion

Two models, SDRand Coates-Timur, were used to evaluate the permeability (Eq. 2 and 3). By comparing and adapting the obtained permeabilityby core data, scale factor C for the models was 0.35 and 0.12, respectively. Results indicate that the best conformity is between Coates-Timur and core permeability. SDR permeability, is less reliable than Coates-Timur method due to the sensitivity of this model to hydrocarbon. In gas zones, DMRPin combination with Coates-Timur equation can provide a better estimation of permeability than TCMR. Therefore, the model proposed for obtaining the permeability in this formation is Coates-Timur model using DMRP porosity.

Based on core data, dolomite zone has higher permeability than Coates-Timur model due to the presence of open horizontal fractures.The coefficients of three empirical methods were calculated by trial and error through comparing with core permeability. Coates-Dumanoir method shows the best correlation coefficient (R^2=0.38).Permeability estimation by fuzzy logic method (R^2= 0.42)is more reliable than CMR method (R^2= 0.4) and Coates-Dumanoirempirical method (R^2= 0.38).Generally, by comparing the core permeability with permeability obtained by applied methods, CMR, empirical formula and fuzzy logic, acceptable conformity was not attained and such inconformity is due topresence of complex opening systems, nature of porosities and indirect relation between porosity and permeability in carbonate reservoir rock (Table 3).

Table.3.The results of permeability estimation

Method	CMR	Empirical Methods				Fuzzy Logic
		Morris-Biggs	Timur	Coates	Coates-Dumanoir	
Correlation coefficient	40%	32%	27%	33%	38%	42%

5. Conclusions

The results of this study are as follows:

1. By comparing the permeability data of different methods, it is demonstrated that they are strongly influenced by carbonate reservoir, presence of complex opening systems, nature of porosities and indirect relation between porosity and permeability in carbonate reservoir rock.
2. By comparing the cross plot of core porosity against its permeability the type of porosity in the studied part can be determined among interparticle, moldic, vuggy and to some extent the fractured.
3. The core permeability points against porosity resulted from CMR(TCMR) indicated that porosity trends have no conformity with each other, which is due to gaseous state of the studied reservoir; therefore, a parameter called DMRP was used for estimating the porosity.

4.It can be concluded that when there is no PHIT and PHIE porosities, DMRP porosity can be used for estimating the porosity. Because porosity resulted from NPHI and DPHI diagrams are influenced by gas, DMRP porosity can be used to predict the porosity.

5.Due to the presence of pore-size distribution, pore system and distribution of porosities in the reservoir rock, it seems that it is better to combine the results of T_2 distribution curve with thin-section, so their accuracy can be approved.

6.The Timur-Coates and SDR equations, which were used to derive permeability from CMR log, were not successful in carbonate. This mismatch is attributed to the high sensitivity of $T_{2cutoff}$ to pore types in carbonate rocks. Unlike sandstones in which petrophysical properties are highly dependent on porosity, there is no such a simple relationship in carbonate rocks due to their complex mineralogy and pore types system. For this reason, pore types classification and calibration of $T_{2cutoff}$ values with capillary pressure data are expected to give better results in calculating permeability.

7.This mismatch is attributed to the uncertainty in determination of T_2 distribution cut-off separate free fluids from bound fluids. Normally, T_2 cutoff value is considered as 92 ms for carbonate rocks. However, this value could vary from 90 ms to 700 ms due to reasons such as lithology heterogeneity, complex pore type system, and presence of isolated secondary porosities like moldic and vuggy in carbonate reservoirs.

8.The correlation between K_{Timur} permeability is higher than K_{SDR}. This could be attributed to the following reasons:

Changes in T_2 distribution which affect T_{2LM} are not considered in K_{Timur} while being considered for K_{SDR}. Irrespective of K_{SDR}, the Timur-Coates permeability is not affected by formation fluid type. Change in fluid type will cause a change in T_2 distribution curve and consequently a change in T_{2LM}, whereas BVI and BVM values will remain unchanged.

9.Therefore, the model proposed for the permeability prediction in this formation is Timur model using DMRP porosity.

10. The results of permeability data were estimated by three empirical methods including Willey and Rose (using Timur and Morris-Biggs coefficients) Coates and Coates-Dumanoir. The coefficients calculated by four formulas by trial and error method seem to have the best correlation with core points and the best correlation coefficient was related to Coates-Dumanoir method.

11. Permeability data estimated by Fuzzy logic method indicates the relative predominance of this method compared with CMR and Coates-Dumanoir Empirical methods. In this study, the number of core permeability points was limited. So, there were not sufficient data for training Fuzzy model. This problem associated with rock heterogeneities could lead to unusual responses of Fuzzy model (over-estimation or under-estimation).

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